

The formula for the connection of common attributes of things

Jieqing HOU^{1, 2*}

¹ Institute of Mountain Hazards and Environment, Chinese Academy of Sciences, Chengdu 610041, China

² School of Engineering Science, University of Chinese Academy of Sciences, Beijing 100049, China

Abstract:

Objective: This article aims to construct a general formula from a philosophical perspective to describe the connections between the common attributes of things, providing preliminary insights into complex phenomena such as chaos theory and deep learning.

Methods: Through conceptual analysis and theoretical deduction, a mathematical model based on attribute quantities is established to quantify the connections between things.

Results: The study finds that the formula is applicable to analyzing chaotic phenomena in physics and complex systems in social sciences, potentially aiding in explaining difficulties in human learning and the accuracy improvement of deep learning models.

Limitations: The theoretical construction lacks extensive empirical support, and the determination of attribute quantities and standards poses practical challenges.

Conclusions: The common attribute connection formula offers a new tool for understanding the connections between things, and future research should focus on empirical validation and interdisciplinary applications.

Keywords: Common Attributes; Connection; chaos

* Corresponding author: Jieqing Hou (E-mail: houjieqing@imde.ac.cn)

Introduction

Everything is universally connected, and there is no such thing as an absolutely isolated entity^[1]. The entire world is an interconnected unity^[1]. Addition, subtraction, multiplication, and division constitute the connections of the world. From a certain perspective, science is about exploring the connections between things to understand the world and summarize laws. The connections between things are manifested through the interactions and relationships of their attributes. There are basic common attributes and basic distinct attributes between things. There are also common attributes and distinct attributes between things. The common attributes between things can be formed by combining basic common attributes and basic distinct attributes, and distinct attributes can also be formed by combining basic common attributes and basic distinct attributes. The connections between things are divided into common attribute connections and distinct attribute connections. Just as there are seven fundamental dimensions in physics, these seven fundamental dimensions are the basic attributes in physics, and these dimensions can be combined to form new dimensions, which means that basic attributes can also form new attributes, including both common and distinct attributes. Here, attributes include both objective and subjective attributes. Objective attributes refer to the inherent properties of things that do not depend on human consciousness or perception. Objective attributes exist objectively, whether or not they are observed or perceived by people. For example, the mass, volume, and shape of an object are its objective attributes. Subjective attributes refer to the properties that people assign to things based on personal feelings, emotions, values, cultural backgrounds, and other factors. These attributes are subjective because they depend on human consciousness and perception, and different people may have different subjective attributes for the same thing. For example, different people may have different aesthetic evaluations for the same painting, and this aesthetic feeling is a subjective attribute.

Science includes both natural science and social science. Natural science research currently focuses on the discovery and application of distinct attribute connection formulas, such as Newton's second law, which connects Newtonian force, mass, and acceleration; the electric field force formula, which connects Newtonian force, charge, and electric field strength; Euler's identity, which connects rational numbers, irrational numbers, and imaginary numbers; and Faraday's law of electromagnetic induction, which connects electricity and magnetism. The grand unified theory that scientists are currently seeking to find will connect gravitational force, electromagnetic force, strong interaction, and weak interaction. These formulas all connect the distinct attributes of things. The hallmark of distinct attribute connection formulas is that they contain different attributes within a single formula: in physics formulas, this is marked by the presence of different dimensions; in other formulas, it is marked by the presence of different units; in mathematics, it is marked by the presence of numbers with different attributes, such as the rational numbers, irrational numbers, and imaginary numbers in Euler's identity. Some famous formulas in social science also focus on the exploration of distinct attribute connection formulas, and social scientists often ratioize these distinct attributes to connect them. These distinct attribute connection formulas have allowed us to understand the world, promoted the development of civilization, and constitute the science of today.

Method

However, the connection of common attributes, as a universal presence in the connections between things, is the underlying logic of the world's operation along with the connection of distinct attributes, and together they constitute this orderly world. The connection formula of common attributes is also worth exploring, and discovering and establishing it can greatly assist us in exploring the world. Based on the philosophical division of the properties of things, I attempt here to establish the connection formula for common attributes.

Let a common attributes between different things be $A_1, A_2, A_3, \dots, A_{n-1}, A_n$, and call A the attribute quantity. Taking the standard quantity of attributes as B , then A_i/B is a dimensionless number, representing the multiple of the attribute quantity relative to the standard quantity. This is to transform the attribute quantity into familiar numbers for us, facilitating understanding. Thus, let the dimensionless numbers corresponding to each attribute quantity be $M_1, M_2, M_3, \dots, M_{n-1}, M_n$. Then let $X_0 = M_1/M_1$, $X_1 = M_2/M_1$, $X_2 = M_3/M_2$, $X_3 = M_4/M_3$, ..., $X_{n-1} = M_n/M_{n-1}$, $X_n = M_{n+1}/M_n$. Although we often do not know the specific values and units of the attribute quantities and standard quantities, things objectively exist, so attribute quantities must exist, and standard quantities must also exist. Thus,

$$A_i = A_1 \prod_{i=1}^n X_{i-1} = A_m \prod_{i=m}^n X_{i-1};$$
$$X_{i-1} = \frac{M_i}{M_{i-1}} = \frac{A_i}{A_{i-1}}; \quad A_i = B M_i;$$

The lack of connection between things is also a kind of connection, so we should consider the situation where distinct attributes are mixed with common attributes. Moreover, the fact that distinct attributes occupy positions in the arrangement is also a kind of connection. When a distinct attribute quantity is in position i , at this time $A_i=0$, $M_i=0$, and we take $X_{i-1}=1$; when there is only one distinct attribute quantity, $X_i=M_{i+1}/M_{i-1}$, and other positions' X values are calculated normally; when n distinct attribute quantities appear consecutively, at this time we let the positions of the distinct attribute quantities be $i, i+1, i+2, i+3, \dots, i+n-2, i+n-1$, at this time the corresponding positions A, M values are all 0. At this time we take $X_{i-1}=X_i=X_{i+1}=\dots=X_{i+n-3}=X_{i+n-2}=1$, $X_{i+n-1}=M_{i+n}/M_{i-1}$, and calculate the X values at other positions normally. This is the connection formula for the common attributes of things. This connection formula is applicable to both stationary and moving systems of objects.

Application

The current chaos theory is an example of the connection formula for the common attributes of things, and the chaotic phenomena in nonlinear dynamics follow the connection formula for the common attributes of things. In this context, each element in the sequence at different positions is regarded as a new independent entity. The elements at various positions in the sequence are connected through their common attributes, hence they adhere to the formula for the connection of common attributes. The Lorenz map expression is given by $Z_{n+1}=f(Z_n)^{[2]}$. According to the connection formula for common attributes, the Lorenz map expression should be $Z_{n+1}=C_n Z_n$, where C is a dimensionless number, representing the ratio of the next characteristic to the previous one. Although $C_n Z_n$ is a form of $f(Z_n)$, it is more explicit, but it does not exclude the possibility that the value of C is related to Z_n . The Lorenz map implies that

$C_n = Z_n f(Z_n)$, meaning that the value of C always satisfies this relationship. This mapping predicts a characteristic that changes over time, and a sequence of characteristics will appear over time, which belongs to the common attributes. The Logistic Map expression is given by $X_{n+1} = rX_n(1-X_n)$ ^[3], which means $X_{n+1}/X_n = r(1-X_n)$. Based on the connection formula for common attributes, the form should be $X_{n+1}/X_n = C_n$, that is, in the Logistic Map expression, $C_n = r(1-X_n)$, indicating that the value of C here is related to X_n , but it does not prove why the value of C is related to X_n . This statement indicates that C_n satisfies the relationship $C_n = r(1-X_n)$, meaning that when r is a constant, the value of C is linearly related to the value of X . The formula for the connection of common attributes is a universally followed formula for chaotic phenomena, hence the characteristics of turbulence can also be described using the formula for the connection of common attributes. An important characteristic of chaotic phenomena is the presence of topological transitivity, and the essence of this topological transitivity is the transmission of common attributes.

The current chaos theory has evolved from observed phenomena, using various mappings to describe different chaotic phenomena. Chaos theory is a constantly developing field. In reality, actual chaotic phenomena do not strictly follow a certain mapping for the entire sequence; only parts of the sequence follow that mapping, while other parts exhibit different dynamic behaviors. Utilizing the formula for the connection of common attributes can fully describe the phenomenon, whereas mappings cannot fully describe it.

Stationary systems of things also adhere to the formula for the connection of common attributes. For now, we will not consider the connections based on differing attributes between things, but only those based on their common attributes. There are often multiple common attribute quantities among stationary things, and choosing different common attribute quantities can lead to different connections between them.

If we only consider the objective attribute connections between things, these objective connections do not involve the participation of a subject, and such connections are not subject to human will. Because there are multiple objective common attributes between things, there are also multiple objective common attribute connections. Since there is no subject participation, objective attribute connections do not have standards. At this time, the formula for objective common attribute connections is:

$$A_i = A_1 \prod_{i=1}^n \frac{A_i}{A_{i-1}} = A_m \prod_{i=m}^n \frac{A_i}{A_{i-1}}$$

If the participation of a subject is considered, then there are standards, and there may be connections based on subjective attributes, while objective attributes still exist. Since the subject has certain feelings towards things, it can assign subjective attributes and perspectives to things. The perspective is also the attribute of things that the subject focuses on. Here, the subject can be humans, animals, deep learning models, objects, or anything that can assign standards to things. For example, for a deep learning model, the standard can be said to be its ability to solve various tasks. At this time, the common attribute among various tasks is the difficulty level of each task. At this time, tasks are connected through their difficulty levels. The perspective of the deep model is the attribute of task difficulty. The size of the problem-solving ability is the magnitude of the standard quantity.

Here is an attempt to explain the phenomenon of "circumstances change with the mind."

When we face a series of challenging things, if we change our perspective and focus on another objective common attribute of these challenges, the objective common attribute connections among these challenging things will shift to another type of objective common attribute connection. This involves changing the category on the objective common attribute quantity A, at which point the standard quantity B and the dimensionless number M will both change. If we adjust ourselves and change our ability to deal with these issues, which is to say, change the magnitude of the standard quantity, then although the objective connections among these challenging things remain the same, our subjective feelings have changed, giving us the sensation that the environment has changed. This involves changes in the standard quantity B and the dimensionless number M, while the objective common attribute quantity A remains unchanged, meaning the objective common attribute connections of things have not changed. If we assign subjective attributes to these challenging things, the common attribute connections between them become subjective common attribute connections. When we assign another subjective common attribute to these challenging things, the connections between them become another type of subjective common attribute connection. In all these cases, it is the change in the subject that makes us feel the environment has changed, while the actual objective environment has not changed.

People often have a clear understanding of things within their capabilities, a vague understanding of things slightly beyond their capabilities, and almost no understanding of things far beyond their capabilities. When facing a pile of chaotic things, due to the existence of various different common attributes among things, people can change the connections and arrangements between things by focusing on different common attributes according to their subjective interests. When studying a book, the knowledge points in the book can be arranged according to their appearance order or according to the difficulty we subjectively perceive in acquiring them. From the perspective of the connection formula for common attributes, it can be explained why some knowledge points seem difficult to grasp at first, but after skipping them and learning other knowledge, one may suddenly understand them when returning to study them later. When the knowledge points in the book are arranged according to the subjective difficulty of acquiring them, the following mathematical model can be obtained.

Let the knowledge points be arranged in order of increasing subjective difficulty in acquisition, denoted as $A_1, A_2, A_3, \dots, A_{n-1}, A_n$. According to the connection formula for common attributes, we can derive:

$$A_i = A_1 \prod_{j=1}^i X_{i-j} = A_m \prod_{j=m}^i X_{i-j}, \quad X \geq 1$$

That is to say, the relative difficulty of acquiring knowledge points increases the later you get, and if the difficulty of knowledge point A_1 is very high from the beginning, then its impact on subsequent learning will be significant, similar to the "butterfly effect" in chaotic systems. Since humans have the ability to learn, knowledge points within their learning capacity can be easily acquired, while those beyond their capacity can also be acquired but with greater difficulty. Suppose a person's learning capacity is at A_3 , meaning they can easily acquire knowledge points below the A_3 level. The relative difficulty of knowledge points below the A_3 level can be arranged according to the subject's subjective feelings. The difficulty for them to acquire A_6 is $X_3X_4X_5$, and the difficulty to acquire A_9 is $X_3X_4X_5X_6X_7X_8$. Since human learning

capacity can grow through learning, when one can integrate and apply the knowledge they have learned, their learning capacity will increase, just as the learning capacity improves from A_3 to A_4 . The knowledge points that were originally difficult at level A_4 can now be easily grasped, resulting in a sudden feeling of enlightenment. At this point, the difficulty of acquiring A_6 becomes X_4X_5 , and the difficulty of acquiring A_9 becomes $X_4X_5X_6X_7X_8$, further reducing the difficulty of acquisition. With further improvement in learning capacity, the difficulty of acquiring knowledge points A_6 and A_9 will continue to decrease. In theory, human learning capacity can continue to improve, but human energy and lifespan are limited, so learning capacity will eventually level off at a certain point. However, if a person's learning capacity is at A_9 , but X_9 is infinitely large or so large that it is insurmountable, then their learning capacity will stop at A_9 . If a book contains a knowledge point that is insurmountable and this knowledge point is the foundation for learning subsequent knowledge, then a person's study of this book may stop here. Some people start with a higher learning capacity compared to others, so two people's feelings when facing the same book are different. If all the relative difficulties of the knowledge points in the book are within M 's capacity, then M will study with ease and quickly master the knowledge points of the book. Similarly, if all the knowledge points in the book are beyond N 's capacity, it will be very difficult to learn, and even at a certain level of difficulty, the learning will come to a halt.

Why is it so difficult for the accuracy of deep learning models to improve just a little bit in the later stages? The connection formula for the common attributes of things can provide an explanation. Deep learning models also have a certain ability to solve problems, which can easily solve problems within the model's capabilities, and problems beyond the model's capabilities can also be solved, but they are more difficult to solve. I am not sure whether current deep learning models have the ability to continuously improve their learning ability through learning, perhaps it exists, perhaps this function is still very weak at present. But for now, deep learning models at least do not fully possess this ability, and future development should focus on the development of this function. When deep learning models have this ability, it marks a new stage of development for deep learning models, that is, they have the ability to think, learn, and improve themselves. When using deep learning models to extract image features, all features will be automatically sorted from easier to extract to more difficult to extract according to the model's extraction ability. If all features are within the model's extraction capabilities, then the model can easily extract all features. If the model's extraction ability is at level A_5 , and the highest difficulty of subsequent features is at level A_8 , then the difficulty of extracting to A_8 is $X_5X_6X_7$. We only know that X is greater than or equal to 1, but we do not know the exact value of X . However, it is clear that without the ability for autonomous learning improvement in the model, the difficulty of extraction increases the further we go, potentially to the point of infinity. This explains why deep learning models, which do not continuously enhance their capabilities, find it increasingly difficult to complete tasks beyond their capabilities, with the difficulty of such tasks gradually increasing. Therefore, it is very challenging to improve the accuracy of deep learning models even slightly in later stages. When using deep learning models for tasks, we need to understand two aspects: the model's capabilities and the difficulty of the tasks. The formula for the connection of common attributes provides a method for recognizing the internal connections between the objects being extracted. Currently, the formula for the connection of common attributes suggests at least two

developments for deep learning models: one is that deep learning models need to have the ability to learn continuously; the other is that deep learning models should have the ability to perceive tasks beyond their capabilities, that is, they should be able to identify at least the difficulty of the next task beyond their capabilities in order to adopt appropriate strategies.

The formula for the connection of common attributes between things describes a line that connects the common attributes between things. From a mathematical perspective, it also describes the relationship between X_n and n , which can be represented as a discrete function. In a chaotic system, if describing the relationship between X_t and t , it can be represented as a continuous function. The relationship satisfied by Z_{n+1}/Z_n determines the shape of the line, and here Z_{n+1}/Z_n is referred to as the shape kernel. The shape kernel for the Lorenz map is $Z_{n+1}/Z_n=f(Z_n)/Z_n$, and the shape kernel for the Logistic Map is $Z_{n+1}/Z_n=r(1-Z_n)$.

Conclusion

This article, starting from a philosophical perspective, proposes a conceptual framework—the formula for the connection of common attributes of things—intended to quantitatively describe and analyze the universal connections between things. This formula abstracts the attributes of things and expresses them in the form of a mathematical model, providing preliminary insights into the analysis of complex phenomena such as chaos theory, deep learning, and human learning. The research findings of this article reveal the potential application value of the formula for the connection of common attributes in different academic fields, especially in revealing the deep-level interactions and relationships between things in static and dynamic systems. The effectiveness and universality of this formula in practical applications still need to be further verified through interdisciplinary empirical research.

Future Work

Future work in this area should focus on the following key directions: first, conduct extensive empirical tests of the formula for the connection of common attributes to verify its applicability and effectiveness in different academic fields; second, develop computational models and algorithms based on the formula for the connection of common attributes to enhance its application capabilities in solving practical problems; and finally, explore the integration of the formula for the connection of common attributes with other scientific theories to promote the development of interdisciplinary research.

ACKNOWLEDGEMENTS

There are no conflicts of interest, and the views expressed represent my personal opinion only. Like-minded friends are welcome to email me. Kindly offer criticism and correction. If there are any violations of common sense, please forgive me.

References

- [1] Marx, K., & Engels, F. (1848). The Communist Manifesto. People's Publishing House.
- [2] Lorenz, E. N. (1963). Deterministic Nonperiodic Flow. Journal of Atmospheric Sciences, 20(2), 130-141.
- [3] May, R. M. (1976). Simple mathematical models with very complicated dynamics. Nature, 261(5560), 459-467.